

## Sojourn Times of Brownian Sheet

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September 26, 2000

**Keyword and Phrases** Brownian sheet, arcsine law, Feynman-Kac formula  
**AMS 1991 Subject Classification** 60G60.

*This paper is dedicated to Professor Endré Csáki  
on the occasion of his 65th birthday.*

## 1 Introduction

Let  $B$  denote the standard Brownian sheet. That is,  $B$  is a centered Gaussian process indexed by  $\mathbb{R}_+^2$  with continuous trajectories and covariance structure

$$\mathbb{E}\{B_s B_t\} = \min\{s_1, t_1\} \times \min\{s_2, t_2\}, \quad s = (s_1, s_2), t = (t_1, t_2) \in \mathbb{R}_+^2.$$

In a canonical way, one can think of  $B$  as “two-parameter Brownian motion”.

In this article, we address the following question: “*Given a measurable function  $v : \mathbb{R} \rightarrow \mathbb{R}_+$ , what can be said about the distribution of  $\int_{[0,1]^2} v(B_s) \, ds$ ?*” The one-parameter variant of this question is both easy-to-state and well understood. Indeed, if  $b$  designates standard Brownian motion, the Laplace transform of  $\int_0^1 v(b_s + x) \, ds$  often solves a Dirichlet eigenvalue problem (in  $x$ ), as prescribed by the Feynman–Kac formula; cf. Revuz and Yor [6], for example. While analogues of Feynman–Kac for  $B$  are not yet known to hold, the following highlights some of the unusual behavior of  $\int_{[0,1]^2} v(B_s) \, ds$  in case  $v = \mathbf{1}_{[0,\infty)}$  and, anecdotally, implies that finding explicit formulæ may present a challenging task.

### Theorem 1.1

There exists a  $c_0 \in (0, 1)$ , such that for all  $0 < \varepsilon < \frac{1}{8}$ ,

$$\exp\left\{-\frac{1}{c_0}\log^2(1/\varepsilon)\right\} \leq \mathbb{P}\left\{\int_{[0,1]^2} \mathbf{1}_{\{B_s > 0\}} \, ds < \varepsilon\right\} \leq \exp\left\{-c_0\log^2(1/\varepsilon)\right\}.$$

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\*Research supported in part by grants from NSF and NATO

<sup>†</sup>Research supported in part by NSF grant 98-03249

**Remark 1.2**

By the arcsine law, the one-parameter version of the above has the following simple form: given a linear Brownian motion  $b$ ,

$$\lim_{\varepsilon \rightarrow 0^+} \varepsilon^{-1/2} \mathbb{P}\left\{\int_0^1 \mathbf{1}_{\{b_s > 0\}} \, ds < \varepsilon\right\} = \frac{2}{\pi};$$

see [6, Theorem 2.7, Ch. 6].  $\square$

**Remark 1.3**

R. Pyke (personal communication) has asked whether  $\int_{[0,1]^2} \mathbf{1}_{\{B_s > 0\}} \, ds$  has an arcsine-type law; see [5, Section 4.3.2] for a variant of this question in discrete time. According to Theorem 1.1, as  $\varepsilon \rightarrow 0$ , the cumulative distribution function of  $\int_{[0,1]^2} \mathbf{1}_{\{B_s > 0\}} \, ds$  goes to zero faster than any power of  $\varepsilon$ . In particular, the distribution of time (in  $[0, 1]^2$ ) spent positive does not have any simple extension of the arcsine law.  $\square$

**Theorem 1.4**

Let  $v(x) := \mathbf{1}_{[-1,1]}(x)$ , or  $v(x) := \mathbf{1}_{(-\infty,1)}(x)$ . Then, there exists a  $c_1 \in (0, 1)$ , such that for all  $\varepsilon \in (0, \frac{1}{8})$ ,

$$\exp\left\{-\frac{\log^3(1/\varepsilon)}{c_1 \varepsilon}\right\} \leq \mathbb{P}\left\{\int_{[0,1]^2} v(B_s) \, ds < \varepsilon\right\} \leq \exp\left\{-c_1 \frac{\log(1/\varepsilon)}{\varepsilon}\right\}.$$

For a refinement, see Theorem 2.2 below.

**Remark 1.5**

The one-parameter version of Theorem 1.4 is quite simple. For example, let  $\Gamma = \int_0^1 \mathbf{1}_{[-1,1]}(b_s) \, ds$ , where  $b$  is linear Brownian motion. In principle, one can compute the Laplace transform of  $\Gamma$  by means of Kac's formula and invert it to calculate its distribution function. However, direct arguments suffice to show that the two-parameter Theorem 1.4 is more subtle than its one-parameter counterpart:

$$-\infty < \liminf_{\varepsilon \rightarrow 0^+} \varepsilon \ln \mathbb{P}\{\Gamma < \varepsilon\} \leq \limsup_{\varepsilon \rightarrow 0^+} \varepsilon \ln \mathbb{P}\{\Gamma < \varepsilon\} < 0, \quad (1.1)$$

where  $\ln$  denotes the natural logarithm function. We will verify this later on in the Appendix.  $\square$

**Remark 1.6**

The arguments used to demonstrate Theorem 1.4 can be used to also estimate the distribution function of additive functionals of form, e.g.,  $\int_{[0,1]^2} v(B_s) \, ds$ , as long as  $\alpha \mathbf{1}_{[-r,r]} \leq v \leq \beta \mathbf{1}_{[-R,R]}$ , where  $0 < r \leq R$  and  $0 < \alpha \leq \beta$ . Other formulations are also possible. For instance, when  $\alpha \mathbf{1}_{(-\infty,r]} \leq v \leq \beta \mathbf{1}_{(-\infty,R]}$ .  $\square$

## 2 Proof of Theorems 1.1 and 1.4

Our proof of Theorem 1.1 rests on a lemma that is close in spirit to a Feynman–Kac formula of the theory of one-parameter Markov processes.

### Proposition 2.1

There exists a finite and positive constant  $c_2$ , such that for all measurable  $D \subset \mathbb{R}$  and all  $0 < \eta, \varepsilon < \frac{1}{8}$ .

$$\mathbb{P}\left\{\int_{[0,1]^2} \mathbf{1}_{\{B_s \notin D\}} \, ds < \varepsilon\right\} \leq \mathbb{P}\left\{\forall s \in [0, 1]^2 : B_s \in D_{\varepsilon^{\frac{1}{4}-2\eta}}\right\} + \exp\{-c_2 \varepsilon^{-\eta}\},$$

where  $D_\delta$  denotes the  $\delta$ -enlargement of  $D$  for any  $\delta > 0$ . That is,

$$D_\delta := \{x \in \mathbb{R} : \text{dist}(x; D) \leq \delta\},$$

where ‘dist’ denotes Hausdorff distance.

**Proof** For all  $t \in [0, 1]^2$ , let  $|t| := \max\{t_1, t_2\}$ . Then, it is clear that for any  $\varepsilon, \delta > 0$ , whenever there exists some  $s_0 \in [0, 1]^2$  for which  $B_{s_0} \notin D_\delta$ , either

1.  $\sup_{|t-s| \leq \varepsilon^{1/2}} |B_t - B_s| > \delta$ , where the supremum is taken over all such choices of  $s$  and  $t$  in  $[0, 1]^2$ ; or
2. for all  $t \in [0, 1]^2$  with  $|t-s_0| \leq \varepsilon^{1/2}$ ,  $B_t \in D$ , in which case, we can certainly deduce that  $\int_{[0,1]^2} \mathbf{1}_{D^c}(B_t) \, dt > \varepsilon$ .

Thus,

$$\begin{aligned} \mathbb{P}\left\{\exists s_0 \in [0, 1]^2 : B_{s_0} \notin D_\delta\right\} &\leq \mathbb{P}\left\{\sup_{|t-s| \leq \varepsilon^{1/2}} |B_t - B_s| > \delta\right\} + \\ &\quad + \mathbb{P}\left\{\int_{[0,1]^2} \mathbf{1}_{D^c}(B_t) \, dt > \varepsilon\right\}. \end{aligned}$$

By the general theory of Gaussian processes, there exists a universal positive and finite constant  $c_2$  such that

$$\mathbb{P}\left\{\sup_{|t-s| \leq \varepsilon^{1/2}} |B_t - B_s| > \delta\right\} \leq \exp\{-c_2 \delta^2 \varepsilon^{-1/2}\}. \quad (2.1)$$

Although it is well known, we include a brief derivation of this inequality for completeness. Indeed, we recall C. Borell’s inequality from Adler [1, Theorem 2.1]: if  $\{g_t; t \in T\}$  is a centered Gaussian process such that  $\|g\|_T = \mathbb{E}\{\sup_{t \in T} |g_t|\} < \infty$  and whenever  $T$  is totally bounded in the metric  $d(s, t) = \sqrt{\mathbb{E}\{(g_t - g_s)^2\}}$  ( $s, t \in T$ ),

$$\mathbb{P}\left\{\sup_{t \in T} |g_t| \geq \lambda + \|g\|_T\right\} \leq 2 \exp\left\{-\frac{\lambda^2}{2\sigma_T^2}\right\},$$

where  $\sigma_T^2 = \sup_{t \in T} \mathbb{E}\{g_t^2\}$ . Eq. (2.1) follows from this by letting  $T = \{(s, t) \in (0, 1)^2 \times (0, 1)^2 : |s - t| \leq \varepsilon^{1/2}\}$ ,  $g_{t,s} = B_t - B_s$  and by making a few lines of standard calculations. Having derived (2.1), we can let  $\delta := \varepsilon^{\frac{1}{4}-\frac{\eta}{2}}$  to obtain the proposition.  $\square$

**Proof of Theorem 1.1** Let  $D = (-\infty, 0)$  and use Proposition 2.1 to see that

$$\mathbb{P}\left\{\int_{[0,1]^N} \mathbf{1}_{\{B_s > 0\}} < \varepsilon\right\} \leq \mathbb{P}\left\{\sup_{s \in [0,1]^2} B_s \leq \varepsilon^{\frac{1}{4}-2\eta}\right\} + \exp\{-c_2 \varepsilon^{-\eta}\}.$$

Thus, the upper bound of Theorem 1.1 follows from Li and Shao [4], which states that

$$\limsup_{\varepsilon \rightarrow 0^+} \frac{1}{\log^2(1/\varepsilon)} \log \mathbb{P}\left\{\sup_{s \in [0,1]^2} B_s \leq \varepsilon\right\} < -\infty.$$

(An earlier, less refined version, of this estimate can be found in Csáki et al. [2].) To prove the lower bound, we note that

$$\begin{aligned} & \mathbb{P}\left\{\int_{[0,1]^2} \mathbf{1}_{\{B_s > 0\}} ds < 2\varepsilon - \varepsilon^2\right\} \\ & \geq \mathbb{P}\left\{\sup_{s \in [\varepsilon, 1]^2} B_s < 0\right\} \\ & = \mathbb{P}\left\{\forall (u, v) \in [0, \ln(\frac{1}{\varepsilon})]^2 : e^{(u+v)/2} B(e^{-u}, e^{-v}) < 0\right\}, \end{aligned}$$

and observe that the stochastic process  $(u, v) \mapsto B(e^{-u}, e^{-v})/e^{-(u+v)/2}$  is the 2-parameter Ornstein–Uhlenbeck sheet. All that we need to know about the latter process is that it is a stationary, positively correlated Gaussian process whose law is supported on the space of continuous functions on  $[0, 1]^2$ . We define  $c_3 > 0$  via the equation

$$e^{-c_3} := \mathbb{P}\left\{\forall (u, v) \in [0, 1]^2 : \frac{B(e^{-u}, e^{-v})}{e^{-(u+v)/2}} < 0\right\}.$$

By the support theorem,  $0 < c_3 < \infty$ ; this is a consequence of the Cameron–Martin theorem on Gauss space; cf. Janson [3, Theorem 14.1]. Moreover, by stationarity and by Slepian's inequality (cf. [1, Corollary 2.4]),

$$\begin{aligned} & \mathbb{P}\left\{\int_{[0,1]^2} \mathbf{1}_{\{B_s < 0\}} ds < \varepsilon\right\} \\ & \geq \prod_{0 \leq i, j \leq \ln(1/\varepsilon) + 1} \mathbb{P}\left\{\forall (u, v) \in [i, i+1] \times [j, j+1] : \frac{B(e^{-u}, e^{-v})}{e^{-(u+v)/2}} < 0\right\} \\ & = \exp\left\{-c_3 \ln^2(e^2/\varepsilon)\right\}. \end{aligned}$$

This proves the theorem.  $\square$

Next, we prove Theorem 1.4.

**Proof of Theorem 1.4** Let  $\mathcal{D}_\varepsilon$  denote the collection of all points  $(s, t) \in [0, 1]^2$ , such that  $st \leq \varepsilon$ . Note that

1. Lebesgue's measure of  $\mathcal{D}_\varepsilon$  is at least  $\varepsilon \ln(1/\varepsilon)$ ; and
2. if  $\sup_{s \in \mathcal{D}_\varepsilon} |B_s| \leq 1$ , then  $\int_{[0,1]^2} \mathbf{1}_{(-1,1)}(B_s) ds > \varepsilon \ln(1/\varepsilon)$ .

Thus,

$$\mathbb{P}\left\{\int_{[0,1]^2} \mathbf{1}_{(-1,1)}(B_s) \, ds < \varepsilon \ln(1/\varepsilon)\right\} \leq \mathbb{P}\left\{\sup_{s \in \mathcal{D}_\varepsilon} |B_s| > 1\right\}.$$

A basic feature of the set  $\mathcal{D}_\varepsilon$  is that whenever  $s \in \mathcal{D}_\varepsilon$ , then  $\mathbb{E}\{B_s^2\} \leq \varepsilon$ . Since  $\mathbb{E}\{\sup_{s \in \mathcal{D}_\varepsilon} |B_s|\} \leq \mathbb{E}\{\sup_{s \in [0,1]^2} |B_s|\} < \infty$ , we can apply Borell's inequality to deduce the existence of a finite, positive constant  $c_4 < 1$ , such that for all  $\varepsilon > 0$ ,  $\mathbb{P}\{\sup_{s \in \mathcal{D}_\varepsilon} |B_s| > 1/c_4\} \leq \exp\{-c_4/\varepsilon\}$ . We apply Brownian scaling and possibly adjust  $c_4$  to conclude that

$$\mathbb{P}\left\{\sup_{s \in \mathcal{D}_\varepsilon} |B_s| > 1\right\} \leq e^{-c_4/\varepsilon}.$$

Consequently, we can find a positive, finite constant  $c_5$ , such that for all  $\varepsilon \in (0, \frac{1}{8})$ ,

$$\mathbb{P}\{\Gamma < \varepsilon\} \leq \exp\left\{-c_5 \frac{\ln(1/\varepsilon)}{\varepsilon}\right\}. \quad (2.2)$$

This implies the upper bound in the conclusion of Theorem 1.4. For the lower bound, we note that for all  $\varepsilon \in (0, \frac{1}{8})$ , Lebesgue's measure of  $\mathcal{D}_\varepsilon$  is bounded above by  $c_6 \varepsilon \log(1/\varepsilon)$ . Thus,

$$\mathbb{P}\left\{\int_{[0,1]^2} \mathbf{1}_{(-\infty,1)}(B_s) \, ds < c_6 \varepsilon \log(1/\varepsilon)\right\} \geq \mathbb{P}\left\{\inf_{s \in [0,1]^2 \setminus \mathcal{D}_\varepsilon} B_s > 1\right\}.$$

On the other hand, whenever  $s \in [0,1]^2 \setminus \mathcal{D}_\varepsilon$ ,  $s_1 s_2 \geq \varepsilon$ . Thus,

$$\begin{aligned} \mathbb{P}\left\{\int_{[0,1]^2} \mathbf{1}_{(-\infty,1)}(B_s) \, ds < c_6 \varepsilon \log(1/\varepsilon)\right\} &\geq \mathbb{P}\left\{\inf_{s \in [0,1]^2 \setminus \mathcal{D}_\varepsilon} \frac{B_s}{\sqrt{s_1 s_2}} > \frac{1}{\sqrt{\varepsilon}}\right\} \\ &= \mathbb{P}\left\{\inf_{\substack{u,v \geq 0: \\ u+v \leq \ln(1/\varepsilon)}} O_{u,v} > \varepsilon^{-1/2}\right\}, \end{aligned}$$

where  $O_{u,v} := B(e^{-u}, e^{-v})/e^{-(u+v)/2}$  is an Ornstein–Uhlenbeck sheet. Consequently,

$$\mathbb{P}\left\{\int_{[0,1]^2} \mathbf{1}_{(-\infty,1)}(B_s) \, ds < c_6 \varepsilon \log(1/\varepsilon)\right\} \geq \mathbb{P}\left\{\inf_{0 \leq u,v \leq \ln(1/\varepsilon)} O_{u,v} > \varepsilon^{-1/2}\right\},$$

By appealing to Slepian's inequality and to the stationarity of  $O$ , we can deduce that

$$\begin{aligned} \mathbb{P}\left\{\int_{[0,1]^2} \mathbf{1}_{(-\infty,1)}(B_s) \, ds < c_3 \varepsilon \log(1/\varepsilon)\right\} &\geq \prod_{0 \leq i,j \leq \ln(1/\varepsilon)} \mathbb{P}\left\{\inf_{i \leq u \leq i+1} \inf_{j \leq v \leq j+1} O_{u,v} > \varepsilon^{-1/2}\right\} \\ &= \left[\mathbb{P}\left\{\inf_{0 \leq u,v \leq 1} O_{u,v} > \varepsilon^{-1/2}\right\}\right]^{\ln^2(e/\varepsilon)}. \end{aligned} \quad (2.3)$$

On the other hand, recalling the construction of  $O$ , we have

$$\begin{aligned}
& \mathbb{P} \left\{ \inf_{0 \leq u, v \leq 1} O_{u,v} > \varepsilon^{-1/2} \right\} \\
& \geq \mathbb{P} \left\{ \inf_{1 \leq s, t \leq e} B_{s,t} \geq e \varepsilon^{-1/2} \right\} \\
& \geq \mathbb{P} \left\{ B_{1,1} \geq 2e \varepsilon^{-1/2}, \sup_{1 \leq s_1, s_2 \leq e} |B_s - B_{1,1}| \leq e \varepsilon^{-1/2} \right\} \\
& = \mathbb{P} \left\{ B_{1,1} \geq 2e \varepsilon^{-1/2} \right\} \cdot \mathbb{P} \left\{ \sup_{1 \leq s_1, s_2 \leq e} |B_s - B_{1,1}| \leq e \varepsilon^{-1/2} \right\} \\
& \geq c_7 \mathbb{P} \left\{ B_{1,1} \geq 2e \varepsilon^{-1/2} \right\},
\end{aligned}$$

for some absolute constant  $c_7$  that is chosen independently of all  $\varepsilon \in (0, \frac{1}{8})$ . Therefore, by picking  $c_8$  large enough, we can insure that for all  $\varepsilon \in (0, \frac{1}{8})$ ,

$$\mathbb{P} \left\{ \inf_{0 \leq u, v \leq 1} O_{u,v} > \varepsilon^{-1/2} \right\} \geq \exp \left\{ -c_8 \varepsilon^{-1} \right\}.$$

Plugging this in to Eq. (2.3), we obtain

$$\mathbb{P} \left\{ \int_{[0,1]^2} \mathbf{1}_{(-\infty,1)}(B_s) ds < c_6 \varepsilon \log(1/\varepsilon) \right\} \geq \exp \left\{ -c_8 \frac{\ln^2(1/\varepsilon)}{4\varepsilon} \right\}. \quad (2.4)$$

The lower bound of Theorem 1.4 follows from replacing  $\varepsilon$  by  $\varepsilon / \ln(1/\varepsilon)$ .  $\square$

The methods of this proof go through with few changes to derive the following extension of Theorem 1.4.

### Theorem 2.2

Suppose  $\varphi : \mathbb{R}_+ \rightarrow \mathbb{R}_+$  is a measurable function such that (a) as  $r \downarrow 0$ ,  $\varphi(r) \uparrow \infty$ ; and (b) there exists a finite constant  $\gamma > 0$ , such that for all  $r \in (0, \frac{1}{2})$ ,  $\varphi(2r) \geq \gamma \varphi(r)$ . Define  $J_\varphi = \int_{[0,1]^2} \mathbf{1}_{\{|B_s| \leq \sqrt{s_1 s_2} \varphi(s_1 s_2)\}} ds$ . Then, there exist a finite constant  $c_9 > 1$ , such that for all  $\varepsilon \in (0, \frac{1}{2})$ ,

$$\exp \left\{ -c_9 \varphi^2 \left( \frac{\varepsilon}{\log(1/\varepsilon)} \right) \log^2(1/\varepsilon) \right\} \leq \mathbb{P} \{ J_\varphi < \varepsilon \} \leq \exp \left\{ -\frac{1}{c_9} \varphi^2 \left( \frac{\varepsilon}{\log(1/\varepsilon)} \right) \right\}.$$

## Appendix: On Remark 1.5

In this appendix, we include a brief verification of the exponential form of the distribution function of  $\Gamma$ ; cf. Eq. (1.1). Given any  $\lambda > \frac{1}{2}$  and for  $\zeta = (2\lambda)^{-1/2}$ , we have

$$\begin{aligned}
\mathbb{E} \{ e^{-\lambda \Gamma} \} & \leq \mathbb{E} \left\{ \exp \left( -\lambda \int_0^\zeta v(b_s) ds \right) \right\} \\
& \leq e^{-\lambda \zeta} + \mathbb{P} \left\{ \sup_{0 \leq s \leq \zeta} |b_s| > 1 \right\} \tag{2.5}
\end{aligned}$$

$$\begin{aligned}
& \leq e^{-\lambda \zeta} + e^{-1/(2\zeta)} \\
& = 2e^{-\sqrt{\lambda/2}}. \tag{2.6}
\end{aligned}$$

By Chebyshev's inequality,  $\mathbb{P}\left\{\int_0^1 v(b_s) ds < \varepsilon\right\} \leq 2 \inf_{\lambda > 1} e^{-\sqrt{\lambda/2} + \lambda\varepsilon}$ . Choose  $\lambda = \frac{1}{8}\varepsilon^{-2}$  to obtain the following for all  $\varepsilon \in (0, \frac{1}{2})$ :

$$\mathbb{P}\{\Gamma < \varepsilon\} \leq 2e^{-1/(8\varepsilon)}. \quad (2.7)$$

Conversely, we can choose  $\delta = (2\lambda)^{-1/2}$  and  $\eta \in (0, \frac{1}{100})$  to see that

$$\begin{aligned} \mathbb{E}\{e^{-\lambda\Gamma}\} &\geq \mathbb{E}\left\{\exp\left(-\lambda\int_0^\delta v(b_s) ds\right); \inf_{\delta \leq s \leq 1} |b_s| > 1\right\} \\ &\geq e^{-\lambda\delta} \mathbb{P}\{|b_\delta| > 1 + \eta, \sup_{\delta < s < 1+\delta} |b_s - b_\delta| < \eta\}. \end{aligned}$$

Thus, we can always find a positive, finite constant  $c_{10}$  that only depends on  $\eta$  and such that

$$\mathbb{E}\{e^{-\lambda\Gamma}\} \geq c_{10} \exp\left\{-\sqrt{\frac{\lambda}{2}} [1 + (1 + \eta)^2(1 + \psi_\delta)]\right\},$$

where  $\lim_{\delta \rightarrow 0^+} \psi_\delta = 0$ , uniformly in  $\eta \in (0, \frac{1}{100})$ . In particular, after negotiating the constants, we obtain

$$\liminf_{\lambda \rightarrow \infty} \lambda^{-1/2} \ln \mathbb{E}\{e^{-\lambda\Gamma}\} \geq -2^{1/2}. \quad (2.8)$$

Thus, for any  $\varepsilon \in (0, \frac{1}{100})$ ,

$$e^{-\sqrt{2\lambda}(1+o_1(1))} \leq \mathbb{E}\{e^{-\lambda\Gamma}\} \leq \mathbb{P}\{\Gamma < \varepsilon\} + e^{-\lambda\varepsilon},$$

where  $o_1(1) \rightarrow 0$ , as  $\lambda \rightarrow \infty$ , uniformly in  $\varepsilon \in (0, \frac{1}{100})$ . In particular, if we choose  $\varepsilon = (1 + \eta)\sqrt{2/\lambda}$ , where  $\eta > 0$ , we obtain

$$\mathbb{P}\{\Gamma < (1 + \eta)\sqrt{2/\lambda}\} \geq e^{-\sqrt{2\lambda}(1+o_2(1))},$$

where  $o_2(1) \rightarrow 0$ , as  $\lambda \rightarrow \infty$ . This, Eq. (2.7) and a few lines of calculations, together imply Eq. (1.1).  $\square$

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